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ABSTRACT

A small multivariate data set is used to illustrate the usefulness of structure coefficients when interpreting results of educational experiments. Data are analyzed using a multivariate analysis of variance (MANOVA), and results are interpreted in three different ways to determine the contribution of individual variables to prediction: (1) using multiple analyses of variance following a statistically significant MANOVA; (2) using standardized linear discriminant function coefficients; and (3) using structure coefficients. The use of structure coefficients is shown to be superior to the other methods as structure coefficients honor the multivariate reality of the data, minimize experiment-wise Type I error rates, and are not inflated or suppressed by collinearity among variables. Five data tables are included. (Author/TJH)

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USE OF STRUCTURE COEFFICIENTS IN MULTIVARIATE EDUCATIONAL RESEARCH: A HEURISTIC EXAMPLE

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Paper presented at the annual meeting of the Southwest Educational Research Association, Austin, TX, January 25-27, 1990.

ABSTRACT

A small multivariate data set is utilized to illustrate the usefulness of structure coefficients when interpreting results of educational experiments. Data are analyzed using a multivariate analysis of variance (MANOVA), and results are interpreted in three different ways to determine the contribution of individual variables to prediction--(a) using multiple ANOVAs following a statistically significant MANOVA, (b) using standardized linear discriminant function coefficients, and (c) using structure coefficients. The use of structure coefficients is shown to be superior to these other methods as structure coefficients appropriately honor the multivariate reality of the data, minimize experiment-wise Type I error rates, and are not inflated or suppressed by collinearity among variables.

Use of Structure Coefficients in Multivariate Educational Research: A Heuristic Example

Multivariate statistical methods (i.e., methods employing data sets in which the n of dependent variables $\geq$ 2) are desirable in that they not only reduce the risk of high experimentwise Type I error rates associated with studies employing multiple univariate tests, but they also tend to honor the reality of relationships among the variables under study (Fish, 1988). Although the advent of the computer and numerous "user-friendly" statistical packages have made these mathematically-complex multivariate methods available to even the most non-mathematically oriented researchers (Haase & Ellis, 1987; McMillan & Schumacher, 1984), these techniques still account for only a small percentage of statistical techniques used in various educational and psychological research journals (Elmore & Woehlke, 1988; Goodwin & Goodwin, 1985a, 1985b; Willson, 1980).

Goodwin and Goodwin (1985b) suggest two possible reasons for the absence of use of these more advanced statistical methods: (a) that the majority of research questions of importance to educational and psychological researchers are appropriately addressed using less sophisticated univariate or descriptive techniques, and (b) that numerous researchers are unfamiliar with these methods and therefore are less likely to use them. Although less advanced descriptive or univariate statistics are appropriate for certain research situations, many (e.g., Fish, 1988; Hopkins, 1980; Kerlinger, 1986; Thompson, 1986) have argued

convincingly that behavioral research is generally characterized by a complex set of highly interrelated variables, and that multivariate methods best honor the relationships among variables. Consequently, as Kerlinger (1979, p. 208) has noted, one cannot understand contemporary behavioral research without a fairly good understanding of multivariate approaches and methods."

Considering the wealth of scholars who support the appropriateness of using multivariate statistical methods in most behavioral research situations, it would follow that Goodwin and Goodwin's (1985b) second reason for the absence of use of these methods (i.e., that researchers are unfamiliar with these methods) is in many cases the more likely one. Furthermore, even if a researcher has a precursory knowledge of a particular multivariate method, he or she may be hesitant to employ the method knowing that multivariate results are often difficult to interpret, especially when there is a high degree of correlation among the several variables in the dependent variable set.

Bray and Maxwell (1982), Haase and Ellis (1987), Huberty and Morris (1989), and Share (1984) reviewed several statistical techniques useful in dealing with this problem of multivariate "collinearity." Their discussions are particulary appropriate to research situations characterized by a high degree of collinearity among outcome variables, and involving the initial application of multivariate analyses of variance (MANOVAs). For instance, in a research situation employing a MANOVA with three

predictor and two highly-interrelated criterion variables, the researcher may be unsure how to interpret results even if results are statistically significant and of a notable effect size. According to Huberty and Morris (1989, p. 304), at least three interpretation problems can arise from this research situation: (a) the "variable selection problem," i.e., the determination of which of the several variables account for categorical differences among subjects; (b) the "variable ordering problem," i.e., the determination of the relative contribution of each outcome variable to resultant group differences; and (c) the problem of interpreting underlying constructs that can be identified in the variable system structure on the basis of MANOVA results. The third of these interpretation problems (interpretation of underlying constructs) will be addressed here.

A number of techniques for dealing with identification of constructs underlying variables in multivariate research have been suggested. These techniques include (but are not limited to) (a) following up a statistically significant MANOVA with multiple univariate analyses of variance (ANOVA) tests to determine the effect of the variables in the predictor set on each of the outcome variables, (b) interpreting linear composites (i.e., standardized linear discriminant function coefficients) of outcome variables to determine which variables contribute to underlying constructs identified in the study, and (c) interpreting structure coefficients (correlations between each outcome variable and the linear discriminant function). A

brief review of the literature relative to the use of each of these three techniques follows.

MANOVA Followed by Multiple ANOVAs

When a multivariate analysis of variance (MANOVA) yields statistically significant results, many researchers routinely follow up the MANOVA with multiple ANOVAs in an attempt to determine which outcome variables account for the majority of differences across the independent variables. One serious problem with this approach to interpreting MANOVA results is the potential for escalation of the experimentwise Type I error rate (Bray & Maxwell, 1982; Huberty & Morris, 1989; Share, 1984). As Huberty and Morris (1989, p. 306) have noted:

> Whenever multiple statistical tests are carried out in inferential data analysis, there is a potential problem of "probability pyramiding." Use of conventional levels of Type I error probabilities [e.g., 1%, 5%, 10%] for each test in a series of statistical tests may yield an unacceptably high Type I error probability across all of the tests (the "experimentwise error rate").

Thompson (1986) also addresses the problem with escalation of experimentwise error rates when multiple tests are used:

> . . .the experimentwise error rate is a function of the degree of correlation between the variables being studied, and of the number of statistical significance tests conducted based on data from the

> same subjects. The experimentwise Type I error rate will be at least equal to the alpha level choosen [sic] for each individual test. . . .[T]he experimentwise Type I error rate may be as high as 1 - (1 - alpha) raised to the *k* power, where *k* is the number of statistical tests conducted. For example, if 20 *t*-tests using an alpha of .05 are conducted based on data from the same subjects, the experimentwise error rate will range somewhere between 5% and. . .64.2%. (p. 6)

A second problem associated with the use of multiple ANOVAs following a statistically significant MANOVA is that the two analyses address very different research questions (Huberty & Morris, 1989; Share, 1984). Univariate procedures fail to honor the reality of the linear combinations of the several outcome variables being studied in a multivariate research situation, and, in essence, the reality of the behaviors represented by the variables. As Haase and Ellis (1987, p. 405) note, "univariate test statistics. . .are based on the assumption that the correlations among the dependent variables are zero." Hence, in discriminant analysis where the goal is to identify which underlying constructs best account for group differences, "it is unlikely to be the case that the major differences lie solely in single variables, but rather in combinations of variables such as subsets, or differences between subsets" (Share, 1984, p. 352--emphasis in original).

In the words of Thompson (1986, pp. 9-10), "Only methods which simultaneously consider the full network of variable relationships honor a reality in which the full network of variables may operate simultaneously on each other" (emphasis added). Similarly, Eason and Daniel (1989, p. 1) note that the "use of statistical techniques which do not honor the true relationships among the variables under study may cause the researcher to draw inaccurate conclusions about causality or correlation among variables." Haase and Ellis (1987, p. 405) provide an interesting example which illustrates the advantage of maintaining the multivariate reality of experimental variables:

> Height and weight, for example, may be analyzed independently (univariately), and this analysis may yield conclusions about height and weight. An analysis of the optimal linear combination of height and weight (multivariate), however, would probably be interpreted as an analysis of the concept size. Such truly multivariate modeling simply cannot be addressed by separate univariate analyses. (emphasis in original)

Interestingly, these two arguments against interpreting MANOVA results by consulting multiple univariate ANOVA F tests also serve as good arguments for the use of multivariate methods in research situations in which multiple outcome variables are inherently related. [See Fish (1988) and Thompson (1986) for understandable treatises on the importance of using multivariate

methods in behavioral research.] Consequently, considering the problems associated with following up MANOVA with ANOVAs, and the inability of univariate methods to adequately address behavioral reality, Huberty and Morris (1989, p. 302) conclude that this approach to interpreting MANOVA results is "seldom, if ever, appropriate."

Interpreting Discriminant Function Coefficients

A second method for interpreting effects in multivariate analysis of variance is to follow-up the MANOVA with discriminant analysis. Some researchers (e.g. McQuarrie & Grotelueschen, 1971) use the resulting standardized discriminant function coefficients to determine outcome variable contributions to the identification of underlying constructs. Although this method does consider the multivariate relationships among the variables under study, Bray and Maxwell (1982) and Huberty and Smith (1982) caution that the use of these coefficients when outcome variables are highly intercorrelated may lead to erroneous conclusions about the contributions of a given variable. Hence, Bray and Maxwell (1982) have noted, "Discriminant functions can change drastically with the addition or deletion of one or more variables" (p. 345).

Huberty and Morris (1989, p. 304) concur, noting a particular problem with the replicability of MANOVA results when interpreting discriminant function coefficients:

> What a good variable subset or a relatively good individual variable is depends upon the collection

of the variables in the system being studied. How well the proposed selection and ordering results hold up over repeated sampling needs to be addressed with further empirical study. Of course, replication is highly desirable. The rank-order position of a given variable in a system of variables may change when new variables are added to the system. . . .Hence, <u>a conclusion regarding the goodness of a variable subset and the relative goodness of individual variables must be made with some caution</u>. (emphasis added)

<u>Interpreting Structure Coefficients</u>

A third method for interpreting MANOVA results is to consult structure coefficients in addition to or instead of function coefficients. Structure coefficients (or canonical variate correlations) express correlations between each outcome variable and the linear composite of all the outcome variables (i.e., the "synthetic" or "canonical" variate). Since structure coefficients are not affected by variable collinearity, it is proposed that structure coefficients produce more stable estimates of variable contributions than do function coefficients. As noted by Haase and Ellis (1987, p. 411), discriminant function and structure coefficients offer different types of information about the relationship of variables in a given study:

The discriminant function coefficients reflect the

> unique contribution of any dependent variable <u>over and above that of the remaining dependent variables</u>. The structure coefficient reflects the total contribution of any dependent variable to the linear composite <u>without taking into consideration its relation to or redundancy with the other dependent variables</u>. In this sense, the structure coefficients are akin to factor loadings.
> (emphasis added)

A number of researchers (e.g., Huberty, 1975, 1984; Huberty & Morris, 1989; Kerlinger & Pedhazur, 1973; Meredith, 1964; Spector, 1977; Thompson & Borrello, 1985) have recognized the usefulness of structure coefficients in interpreting results of educational experiments. Thompson and Borrello (1985) provided a demonstration of the superiority of structure coefficients over regression beta weights in a univariate (one dependent variable) research situation involving a high degree of collinearity among predictor variables. Similarly, Huberty and Morris (1989) demonstrated the superiority of structure coefficients over linear discriminant function coefficients in the multivariate case.

Interestingly, however, not all researchers and statisticians agree that structure coefficients are necessarily superior to discriminant function coefficients. For instance, Haase and Ellis (1987, p. 411) note:

> When structure coefficients were first proposed,

> there was some expectation that they would be more stable indexes than the discriminant function coefficients; however, the existing empirical evidence has neither confirmed nor disconfirmed this expectation.

In a review of several studies which have compared the stability of the two types of coefficients in cross-validation applications, Bray and Maxwell (1982), noted that these studies have produced mixed results. However, Bray and Maxwell note that in several of the studies the superiority of structure coefficients is closely linked to the degree of correlation among the variables under study, suggesting that when variables are highly correlated (as often they are in multivariate behavioral research), structure coefficients may be the better coefficients to use in interpreting research results.

It is important to note that it is often valuable to consult both sets of coefficients in a given analysis (Bray & Maxwell, 1982; Thompson & Borrello, 1985); however, as Bray and Maxwell (1982) and Thorndike (1978) conclude, structure coefficients may be the more important coefficient to use in interpreting the substantive nature of the synthetic variable composite as structure coefficients better honor the reality of the relationships among the variables under study. Consequently, Thompson (1988, p. 18) asserts:

> In an artificial forced-choice world in which only one coefficient could be consulted, structure

coefficients might be preeminent; in the real world both coefficients should be consulted in interpretation. Interpretations based solely on function coefficients should be eschewed.

A Heuristic Example

In an effort to investigate the relative merit of the three aforementioned approaches to interpreting MANOVA results, the present study employed a small hypothetical multivariate data set. For the sake of simplicity, a one-way design was used, with experimental condition serving as the three-level predictor variable. Three continuous criterion variables (scores on three subtests in an achievement battery) were specified. Data were analyzed for 36 subjects. These data are presented in the first five columns of Table 1. Following the MANOVA the three interpretive procedures were employed.

The multivariate analysis of variance was conducted using the SPSSx MANOVA procedure. The results of this analysis are presented in Table 2. The analysis yielded a statistically significant ($p < .01$) multivariate F of 4.03. Wilks' lambda for the analysis was .5176, indicating an effect size of approximately 48%. The results of the three follow-up ANOVAs are presented in Table 3.

INSERT TABLES 1, 2, AND 3 ABOUT HERE

Only the ANOVA for dependent variable SCORE3 yielded a statistically significant ($p < .001$) F of 11.81 with an effect

size of 41.71%. In addition to being statistically nonsignificant, the results of the remaining two analyses are also far from noteworthy, with effect sizes of only 4.00 and 8.92%. These results indicate that the SCORE3 variable contributed most heavily to the differences in subjects across the levels of the independent variable. However, as previously noted, the "multiple ANOVAs" interpretive approach fails to address the "linear combination" issue when determining variable contributions. In addition, considering that a total of four significance tests were conducted using the same data set, the resulting experimentwise alpha for these analyses [1 - (1-alpha)^k] using a testwise alpha of .05 is approximately 18.55%, greatly increasing the original 5% chance that the statistically significant results occurred by chance.

A discriminant analysis of the data yielded two discriminant functions, which may be interpreted as representing two underlying composite constructs represented by the data. Standardized discriminant function coefficients and canonical variate structure coefficients for this analysis are presented in Table 4. Consulting the two sets of function coefficients, one would conclude that SCORE3 weights most heavily on the first function, that SCORE1 weights heavily on the second function, and that the near-zero weights associated with SCORE2 indicate that it does not contribute substantially to either function.

<u>INSERT TABLE 4 ABOUT HERE</u>

However, consulting the structure coefficients (which are not affected by collinearity among the variables), the conclusions are somewhat different, suggesting that the second synthetic variable is characterized by both the SCORE1 and SCORE2 variables. Hence, although both analyses serve to identify two distinct constructs underlying the outcome variables, the nature of the second construct is interpreted differently with the two types of coefficients. By consulting only the function coefficients in this example, the researcher may have been prone to eliminate the SCORE2 variable from future research upon the erroneous conclusion that it does not contribute much to either underlying construct.

In order to investigate further the difference in interpreting results using function and structure coefficients, two additional discriminant analyses were run, each adding an additional achievement score variable to the original outcome variable set. Scores for these two additional variables (SCORE4 and SCORE5) are presented in the last two columns of Table 1. The resultant function and structure coefficients for these two additional discriminant analyses are presented in Table 5.

INSERT TABLE 5 ABOUT HERE

Consulting the function coefficients for the first of these two analyses (Analysis #2) one might conclude that the first function represents a variable construct characterized by SCORE3 and SCORE4, and that the second construct primarily represents

SCORE1. Again, as in the previous analysis, one might be prone to feel that SCORE2 is an insignificant variable in the study as it does not seem to make a notable contribution to either of the identified functions.

The structure coefficients for this analysis yield a considerably different interpretation, with SCORE3 and SCORE4 correlating highly with with Function I, and with SCORE1, SCORE2, and SCORE4 correlating highly with Function II. As noted in the previous analysis, the effects of collinearity on the outcome variables could lead to a distorted understanding of the statistical results, and the possible exclusion of an important variable (SCORE2) from further study.

The final analysis (ANALYSIS #3) also yielded interesting results. Utilizing the function coefficients, one would identify two underlying constructs, one characterized by SCORE2, SCORE3, SCORE4, and SCORE5, and the other characterized only by SCORE1. It is particularly interesting that with the addition of SCORE5 to the outcome variable set, SCORE2, which had previously weighted very minimally on either of the functions, now appears to be very strongly identified with Function I. Hence, as previously noted, the addition of a single variable can sometimes have notable effects on the magnitude of the resultant discriminant function coefficients (Huberty & Morris, 1989). Utilizing the structure coefficients, one would associate the SCORE3 and SCORE5 variables with Function I, and the remaining three variables with Function II.

Discussion

The present study sought to investigate three methods for assessing the nature of constructs underlying synthetic variables identified in multivariate analyses of variance. Use of multiple ANOVAs following the initial statistically significant MANOVA identified one variable as contributing significantly to the multivariate results. The two multivariate approaches (interpretation of discriminant function coefficients and interpretation of the resultant canonical variate structure coefficients) indicated that other variables were also worthy of consideration, and suggested the validity of criticisms regarding the appropriateness of the use of univariate ANOVAs in the interpretation of multivariate results.

Although there were some similarities in the interpretation of underlying constructs using function versus structure coefficients, there were also some striking differences. First of all, although the structure coefficient method of interpretation indicated the appropriateness of considering the SCORE2 variable in all three of the analyses, this variable did not obtain a notable weight until the third analysis using the function coefficient method. Since function coefficients tend to be affected by collinearity, it is likely that this variable failed to obtain a notable discriminant function weight in the prior two analyses due to a "suppressor effect" by one of the other outcome variables. Secondly, the new variables introduced in the second and third analyses tended to obtain their higher

function weights on the first discriminant function, yet these variables were more equally distributed across the two functions as judged by their structure coefficients. Thirdly, although both sets of coefficients shifted with each analysis, in general the structure coefficients remained more stable. Finally, the two interpretive methods tended to yield different results as the n of outcome variables was increased. Hence, it may be possible that collinearity became a larger issue as more variables were added to the analysis.

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Table 1
Hypothetical Data Set

CASE	EXPERGRP	SCORE1	SCORE2	SCORE3	SCORE4	SCORE5
1	1	3	3	2	0	1
2	1	3	3	0	2	2
3	1	3	3	0	1	1
4	1	3	3	1	2	2
5	1	3	3	2	2	0
6	1	3	3	1	2	1
7	1	3	3	2	2	2
8	1	3	3	1	2	1
9	1	3	3	1	0	2
10	1	3	3	2	1	0
11	1	3	3	2	1	1
12	1	3	0	1	1	0
13	2	3	3	0	1	3
14	2	3	1	3	1	1
15	2	3	2	0	5	2
16	2	3	2	2	3	2
17	2	3	5	2	3	5
18	2	1	2	5	1	2
19	2	4	1	3	4	1
20	2	1	5	3	1	5
21	2	2	4	3	2	4
22	2	2	4	3	2	4
23	2	2	0	3	2	0
24	2	2	2	3	2	2
25	3	5	7	3	5	7
26	3	0	2	3	0	2
27	3	5	5	3	5	5
28	3	0	0	3	0	0
29	3	5	7	3	5	7
30	3	8	8	3	8	8
31	3	3	2	3	7	2
32	3	3	2	3	1	3
33	3	3	2	3	5	3
34	3	3	2	3	6	8
35	3	3	2	3	2	5
36	3	3	2	3	1	0

Table 2
MANOVA Results

Test Name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	.51900	3.73803	6.00	64.00	.003
Hotellings	.86115	4.30577	6.00	60.00	.001
Wilks	.51762	4.02929	6.00	62.00	.002
Roys	.43476				

Table 3
Result of Subsequent ANOVAs
(DF = 2,33)

Variable	Hypoth. SS	Error SS	Hypoth. MS	Error MS	F	Sig. of F	Effect Size
SCORE1	6.05556	61.83333	3.02778	1.87374	1.61590	.214	8.92%
SCORE2	4.66667	112.08333	2.33333	3.39646	.68699	.510	4.00%
SCORE3	19.50000	27.25000	9.75000	.82576	11.80734	.000	41.71%

Table 4
Function and Structure Coefficients for Initial D[illegible]inant Analysis

Variable	Function Coefficients		Structure Coefficients	
	Funct. I	Funct. II	Funct. I	Funct. II
SCORE1	.27229	1.04842	.10023	.99026
SCORE2	.02083	-.12414	.15238	.50838
SCORE3	1.01018	-.08978	.95977	-.27741

Table 5
Function and Structure Coefficients for Subsequent Discriminant Analyses

ANALYSIS #2

Variable	Function Coefficients		Structure Coefficients	
	Funct. I	Funct. II	Funct. I	Funct. II
SCORE1	-.46296	1.21364	.06330	.98365
SCORE2	.02829	-.12103	.10938	.51929
SCORE3	.81054	.04618	.73479	-.13563
SCORE4	.92375	-.20919	.46618	.59609

ANALYSIS #3

Variable	Function Coefficients		Structure Coefficients	
	Funct. I	Funct. II	Funct. I	Funct. II
SCORE1	-.27050	1.22378	.05339	.98247
SCORE2	-.68139	-.14606	.09126	.51759
SCORE3	.70524	.03585	.60996	-.14597
SCORE4	.52673	-.23057	.38755	.58933
SCORE5	.94256	.03299	.46928	.43601